

From Fuzzy Deformable Prototypes to Elastic Patterns: Preliminary proposal*

Ruben Rodriguez-Cardos (ruben.rodriguez6@alu.uclm.es)¹[0000–0002–0294–8343]
and Jose A. Olivas(joseangel.olivas@uclm.es)¹[0000–0003–4172–4729]

Department of Information Systems and Technologies, University of Castilla La Mancha, Ciudad Real, Castilla-La Mancha, Spain

Abstract. Based on previous experience in prediction systems with Fuzzy Deformable Prototypes, improvement in their functioning and deformation capacity is necessary, a new idea/concept for this is proposed. We propose a system with artificial intelligence that is capable of characterizing new situations, within the context of a PhD. thesis, capable of recognizing samples in a cognitive environment, in addition to testing its viability and performance in a non-cognitive environment a preliminary experiment is carried out, classifying handwritten digits from a reference database (MNIST) with a good success rate.

Keywords: Pattern Recognition · Elastic Patterns · Enginer Strain · Springs · Intelligent Data Analysis · Deformable Prototypes.

1 Motivation/Introduction

The motivation for this work arises from different points:

1. An article by H. Bremermman[1], where he proposes the *Deformable Prototypes*.
2. Fuzzy Prototypes proposed by Lotfi A. Zadeh [8].
3. Starting from points 1 and 2, the Fuzzy Deformable Prototypes proposed by J.A. Olivas [5], these have been applied in a wide number of problems in different fields successfully. However they have a *bottleneck*, they depends on a single parameter, the *degrees of representativeness*.

This work arises especially on the basis of points 1 (with a more focused approach to this point and the use of physics) and 3 of the previous list. As entry point, a handwritten digit recognition through a classic Fuzzy Pattern system (based on the concept of Mask[6]) was done. For these reasons, the main objective of this thesis is: *Improve the application of Fuzzy Deformable Prototypes and the creation/use of a new concept to improve their deformation capacity*, we will call this new concept: **Elastic Patterns**.

* This work has been partially supported by FEDER and the State Research Agency (AEI) of the Spanish Ministry of Economy and Competition under grant MERINET: TIN2016-76843-C4-2-R (AEI/FEDER, UE).

H. Bremermann proposed that a set of equivalent classes can be represented by individual members. Furthermore, if a pattern is equivalent to a class and a series of *affine transformations*, we can try to represent that class by an individual member of it. In that case, these individual members can be called **prototype** [1]. A prototype can be defined by a set of parameters, a *parametric representation*. Combining the work of H. Bremermann and R. Hodges a *matching function* was defined, this function is able of classifying samples from a universe U into one of the existing labels (classes) in that universe.

On the other hand, Lofti A Zadeh proposed that a fuzzy prototype is not an element, but the set of a good, poor and borderline element of a category. *Prototypicality* is a matter of degree. A fuzzy set A can be defined as the degree of membership of selected elements previously divided by the elements. So, a prototype A is a fuzzy set defined by the degree of membership of selected elements previously divided by the prototypes of the elements:

$$PT(A) = High/PT(A_{Good}) + Medium/PT(A_{Borderline}) + Low/PT(A_{Poor})$$

Fuzzy Deformable Prototypes can be described as a linear combination Fuzzy Prototypical Categories (described as tables of attributes), extending the Deformable Prototypes to the case of affinity with more than one Fuzzy Prototypical Category the definition of a real situation would be:

$$C_{real}(w_1...w_n) = | \sum \mu p_i(v_i...v_n) |$$

2 Elastic Patterns

In order to improve the bottleneck of the Fuzzy Deformable Prototypes and their capacity to deform, a new idea is proposed: *Represent a pattern* (a prototype) *by a set of springs and deform these, simulating the physical deformation that will be produced in a real spring*, this is carried out generating a deformation, by contracting or stretching, each spring individually. Measuring the deformation that the springs suffer is one of the most important aspects of this new idea. So, the *Elastic Patterns* generate a deformation on two levels in order to match perfectly with a new sample to be recognized:

- **At the level of the parameter** (spring/parameter deformation): Calculated using the concept of *Engineering Strain*. Used to measure the deformation of a spring on a single axis, obtaining the deformation suffered in function of its initial length, the deformation causes that the final length of the spring is n times the initial length[3]. Parameters that are most deformed individually should add more value to the total deformation. For example: The deformation suffered by a spring that measures 1 cm. and deforms 1 cm. more is much greater than the suffered by a spring of 20 cm. and deforms 1 cm. more.

- **At the level of the pattern** (pattern deformation): The calculation of the *Deformation Energy* corresponds to the deformation of the Elastic Pattern. To carry out this calculation a new concept is used, a *Deformation Vector*. Which is based on the concept of *Deformation Tensor*[2]. This concept normally used in mechanics of continuous media and mechanics of deformable solids, with the aim of weighting the change of shape and volume in a body. The *Deformation Energy* that a pattern undergoes to fit perfectly with a real case is the sum of each of the values of the *Deformation Vector*, in other words, the *Deformation Energy* that affects the Elastic Pattern is the sum of the deformation suffered by each parameter.

It is possible to use the following concept, inherited from the Deformable Prototypes:

A sample is classified according to the minimum Deformation Energy required for physically deforming the closest Elastic Pattern.

3 Preliminary Experiments

To test whether the proposed hypothesis makes sense and can work in a both cognitive (closer to the knowledge engineering) and non-cognitive environments, some preliminary experiments is carried out, similar to the digit recognition system described above. MNIST is, de facto, one of the most used databases in image classification and artificial intelligence tasks, due to the quantity, variety and quality of classified samples. It has been used in many projects[4] [7], so it can be considered a reference data set. For this reason, the experiment is being carried out using MNIST. The conditions under which the experiment is carried out are as follows:

- An image database is available ¹, which is a subset of MNIST, consisting of 70,000 images (matrix-coded) of handwritten digits.
- Each sample is coded as a 28 x 28 pixel matrix, whose values will be in the range 0 (a black pixel) to 255 (a white pixel). In addition, each sample has associated with which digit it represents, these digits being numbers from 0 to 9. The samples are centered in the image.
- The training set consists of 60,000 of these random samples, used to generate the different elastic patterns. The test set will be made up of the remaining 10,000 samples.

The results obtained are: the generation time of the elastic patterns is approximately **20 seconds**, success rate is approximately **80%**, and execution time is approximately **90 seconds**.

¹ <https://www.openml.org/d/554>

4 Conclusions

Once the experiment has been carried out, it is possible to draw the following conclusions:

- Conceptually the Elastic Patterns are easy to understand and use. However, the generation of Elastic Patterns depends on each problem and context in which they are applied.
- They are a good way to generate a model that represents reality in a simple way as the previous works on which they are based[1][5].
- Elastic patterns can work with a certain level of uncertainty, as they deform to perfectly match a new situation.
- The high percentage of correct results in the experiments, over 80%, shows that the proposed new concept is viable and that it is possible to use it at a not cognitive environment too.

As future work the following points are proposed: continue to study how data deformation is possible, establish a general method for the generation of Elastic Patterns, and the use of the Elastic Patterns on a more complex database, use them at a cognitive environment. Currently there is already a project in development for the detection of hereditary cancer using Elastic Patterns.

References

1. Bremermann, H.: Pattern Recognition, pp. 116–159. Birkhäuser Basel (1976)
2. Chen, H.: Constructing continuum-like measures based on a nonlocal lattice particle model: Deformation gradient, strain and stress tensors. *International Journal of Solids and Structures* **169**, 177–186 (2019)
3. Chrysaniadis, T.: Evaluation of out-of-plane response of r/c structural wall boundary edges detailed with maximum code-prescribed longitudinal reinforcement ratio. *International Journal of Concrete Structures and Materials* **14**(1) (2020)
4. Deng, L.: The mnist database of handwritten digit images for machine learning research [best of the web]. *IEEE Signal Processing Magazine* **29**(6), 141–142 (2012)
5. Olivas, J.A.: Contribución al estudio experimental de la predicción basada en categorías deformables borrosas. Ph.D. thesis, Universidad Castilla-La Mancha (2000)
6. Rodríguez-Cardos, R.: Reconocimiento óptico de caracteres en escritura manual, chap. 4,5. Universidad Castilla-La Mancha (2017), <https://ruidera.uclm.es/xmlui/handle/10578/15413>
7. Schott, L., Rauber, J., Bethge, M., Brendel, W.: Towards the first adversarially robust neural network model on mnist. *arXiv preprint arXiv:1805.09190* (2018)
8. Zadeh, L.A.: A note on prototype theory and fuzzy sets. *Cognition* **12**(3), 291 – 297 (1982)